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Abstract

Wind power generation has a key role in Spanish electricity system since it is a native source of energy that could help Spain to reduce its dependency on the exterior for the production of electricity. Apart from the great environmental benefits produced, wind energy reduce considerably spot energy price, reaching to cover 16,6 % of peninsular demand. Although, wind farms show high investment costs and need an efficient incentive scheme to be financed. If on one hand, Spain has been a leading country in Europe in developing a successful incentive scheme, nowadays tariff deficit and negative economic conjunctures asks for consistent reductions in the support mechanism and demand wind producers to be able to compete into the market with more mature technologies. The objective of this work is to find an optimal commercial strategy in the production market that would allow wind producer to maximize their daily profit. That can be achieved on one hand, increasing incomes in daily and intraday markets, on the other hand, reducing deviation costs due to error in generation predictions. We will previously analyze market features and common practices in use and then develop our own sale strategy solving a two-stage linear stochastic optimization problem. The first stage variable will be the sale bid in the day–ahead market while second stage variables will be the offers to the six sessions of intraday market. The model is implemented using real data from a wind producer leader in Spain.

Keywords: electricity market; wind producer; stochastic programming.

# I. INTRODUCTION

Nowadays, the electricity production systems of most countries in EU and EEUU states are organized around a competitive electricity market system. In order to participate to the daily market of day D, all qualified energy producers have to submit their sale bids before 10.00 a.m. of day D-1 to the Independent Market Operator (IMO). The IMO then determines the clearing price as the one corresponding to the last generation unit dispatched in order to cover the accumulated demand (single clearing price auction procedure). After the daily market there are a set of intraday markets (six in the case of the Iberian Electricity Market, IEM) where producers can submit both sales and purchases bids in order to adjust their actual generation to the unmatched energy in the daily market or to the deviation from the forecasted production, in the case of renewable energy producers (OMIE (2012)).

Due to the stochastic nature of wind-power generation, the optimal selling strategy of a wind power producer mainly depends on the most recent generation estimates available before each market session closes (both daily and intraday). The simplest and most common way to operate is relying on the last prediction available to formulate sale bid for the daily market and then adjusting the final programming, participating to some intraday markets session only if a considerable error in the prediction is detected during the day.

Generation estimates, constructed internally or by a third party and updated all day long, are the results of meteorological forecasts and, even if sophisticated software have been developed to improve prediction models, they still show a significant variability (between 20 and 30%). Since a forecasting error can determine a penalization for deviation affecting the economic result, it is important to study its distribution and to consider it in the decision process. Another source of randomness is due to imperfect information on market prices since they are very volatile. In spite of that, daily price curves show a sort of regularity in their shape mainly due to typical fluctuations in the demand from some range of hours to the other, distinguishing peak and off-peak hours.

Moreover, systems with a relevant presence of renewable energy in generation mix show yearly seasonality mainly due to water/wind conditions. It is of great importance keep into account these characteristics of the market when formulating a sale bid.

The role of the wind power generation in the electricity energy production system has been studied from many different points of view. The introduction of wind power generation in different national systems is analyzed in Riviere (2010) and MacGill (2010). Holttinen (2005) studies how the rules of the electricity market operation affects profits of the wind power producers. Several authors have considered the problem of the optimal bid of a wind producer to the daily electricity market but disregarding the influence of the intraday markets in this optimal bid. Moreno (2012) considers the optimal bid to the intraday markets for a given known position in the daily market which, to some extent, is the complementary problem to the one considered in this work, where the optimal sale bid to the daily market is found taking into account all the possible positions in the intraday markets. Several optimal bidding strategy for the daily electricity market has been proposed in previous works. Li and Shi (2012) apply an agent-based simulation methodology to explore the incidence in the daily bid of a wind power producer of short-term forecasting accuracy. Pinson et al. (2007) propose and optimal bid strategy based on probabilistic forecast of wind generation. Garcia-Gonzalez et al. (2008) proposed a stochastic programming model to optimize the daily sale bid of a wind power in combination with a pumped-storage facility.  Finally, Morales et al. (2010) propose a stochastic programming model for the optimal sale to the daily market taking into account a simplified representation of the adjustment (intraday) market with just one session.

Contrary to the previous works so far mentioned, this paper proposes a new procedure to find the optimal sale bid to the day ahead market of a wind power producer operating in the IEM taking into account the complete structure of the six IEM's intraday markets. This procedure is based on the stochastic programming methodology and allows maximizing the expected profit of the wind power producer considering both incomes from the daily and intraday markets together with the penalty due to deviation costs. This problem is formulated through a two-stage stochastic programming problem incorporating two sources of randomness, the one in generation forecasts and that in hourly clearing prices, that can be solved conveniently with available commercial optimization software. The model is validated with real market price data coming from the IEM and a wind power generation data of a Spanish wind power producer under several market price conditions, showing the value of the stochastic solution obtained.

# II. MODEL DESCRIPTION

## A. RANDOM VARIABLES.

The random variable $g_i$ is the sum of the generation forecast and the error term of hour i available for daily market D. In the two stage linear stochastic problem it is represented by a set of scenarios $s \in S$ with probability $p^s$. The other random variable $\pi_{ij}$ is the clearing price of hour i in intraday market session j. In the two stage linear stochastic problem it is represented by a set of scenarios $r \in R$ with probability $q^r$.

## B. DECISION VARIABLES.

The decision variable $x_i$ is the quantity of energy to sell in daily market D in hour i. That is the first stage variable because it does not depend neither on error forecast nor on intraday market prices.

The second stage variables $y_{ij}^{s,r}$ are the energy volumes negotiated in hour i of the intraday market j for generation scenario s and price scenario r (see Figure 1). Those are defined on the sets $A(j)$ that define the market window (hour available for adjustments) of any intraday session. For instance, $A(1) = A(2) = \{1,2, \dots ,24\}$, $A(3) = \{5,6, \dots ,24\}$ and so on. Through the adjustments $y_{ij}^{s,r}$ a wind producer can modify its initial sale bid $x_i$ and determine its final daily generation program.

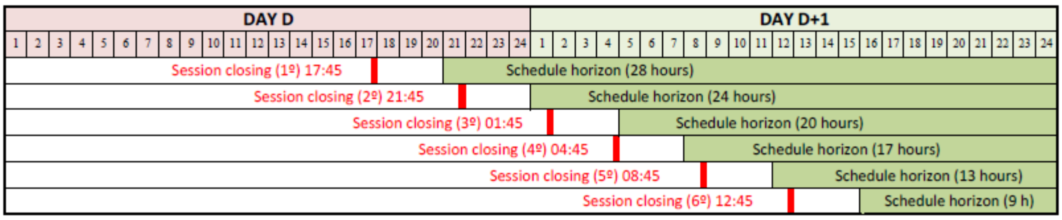


Figure 2: sessions of the intraday market

## B. CONSTRAINTS.

The model includes technical constraints due to market rules and common market practices. These constraints depend on the following parameters:

- $M$: the number of sessions of intraday market;
- $c_i$: the hourly positive deviation cost;
- $\bar{e}_i$: the last generation forecast received before daily market session closes;
- $g_i^s$: the forecasted generation in scenario s;
- $b$: the installed capacity of the wind farm;
- $\gamma_j$: the maximum percentage of total capacity offered in intraday market j;
- $\alpha$: lower bound for the generation bid quantities to the daily market.
- $\beta$: lower bound for bid to the first session of intraday market.

Constraint (1) prescribes to sell in every hour $i$ of day ahead market D at least a certain fraction $\alpha$ of the expected generation $\bar{e}_i$ and, trivially, not to commit more than wind farm installed capacity $b$.

$$\alpha\, \bar{e}_i \le x_i \le b \qquad i = 1,2, \dots ,24 \tag{1}$$

From a merely mathematical point of view, lower bound should be zero. Unfortunately zero for a wind power plant means “unavailable” and consequently it will not be able to participate to any following session of the market.

Moreover, in the Electricity Market Activity Rules at paragraph 10.4 “Notifications of production forecast for each production unit”, the right to require generation predictions to special regime producers is reserved to the regulator. Since he has to grant energy demand and offer to continuously match, if he detects systematic offers lower than registered predictions could consider anti-competitive the behavior of a wind producer (that has priority in the dispatch) and sanction it.

Restriction (2) binds the energy a producer can buy in the first intraday market to a certain percentage $\beta$ of the quantity sold in the daily market.

$$y_{i1}^{sr} \ge -\beta x_i \quad i = 1,2, \dots ,24, \qquad s = 1,2, \dots , S \quad r = 1,2, \dots , R \tag{2}$$

That is a generator has to be able to produce at least a minimum of the energy quantity committed in the daily market. Intraday markets are supposed to be “adjustment markets”: a generator should not systematically buy energy if he is not capable to produce it at all.

Restriction (3) links final production programming to generation forecast $g_i^s$.

$$g_i^s \le\ x_i + \sum_{\forall j \mid i \in A(j)} y_{ij}^{sr} \le b \qquad i = 1,2, \dots ,24 \;\; s = 1,2, \dots , S \;\; r = 1,2, \dots , R \tag{3}$$

The expression $\sum_{\forall j \mid i \in A(j)} y_{ij}^{sr}$ corresponds to the matched energy in all those intraday markets that include hour $i$. Data on wind energy producers’ market behavior show a clear preference for a negative deviation in production associated to a negligible probability to incur in penalization. So we will ask final programming to be greater or equal than forecasted generation at each scenario $g_i^s$ and lower than installed capacity $b$.

The next restriction is establishes that the net position in the market for hour $i$ negotiated at daily market and intraday session 1 to $n$ (that is, the net amount of energy matched in all these sessions, $x_i + \sum_{\forall j \le n \mid i \in A(j)} y_{ij}^{sr}$) cannot be neither negative nor greater than the maximum $b$ he is capable to produce:

$$0 \le x_i + \sum_{\forall j \le n \mid i \in A(j)} y_{ij}^{sr} \le b \qquad i = 1, \dots ,24\, , n = 1, \dots , M, s = 1, \dots , S, r = 1, \dots , R \tag{4}$$

Finally, restriction (5) bounds energy quantity offered into intraday markets to a certain percentage of the installed capacity, decreasing as long as markets close and generation horizon comes closer. That is because market regulator expects the adjustments to be decreasing and size of transactions becoming smaller that a fraction $\gamma_{j+1} < \gamma_j < 1$ of the total capacity $b$:

$$-\gamma_j b \leq y_{ij}^{sr} \leq \gamma_j b \qquad i \in A(j), j = 1, \dots, M, s = 1, \dots, S, r = 1, \dots, R \tag{5}$$

### C. OBJECTIVE FUNCTION.

The utility function of our problem $f(x, y; \pi, g)$ corresponds to the expected value of the daily profit function for a wind power producer with respect to the generation and intraday market price random variables, and can be expressed as:

$$f_{\pi,g}(x, y) = I_{day-ahead}(x) + E_{\pi,g}[I_{intraday}(y)] - E_{\pi,g}[C_{deviation}(x, y)] \tag{6}$$

where:

$$I_{day-ahead}(x) = \sum_{i=1}^{24} \lambda_i x_i \tag{6.1}$$

is the expected income achieved selling energy $x_i$ at the expected clearing price $\lambda_i$ of the daily market.

$$E_{\pi,g}[I_{intraday}(y)] = \sum_{r=1}^{R} q^r \left[ \sum_{j=1}^{M} \sum_{i \in A(j)} \pi_{ij}^r \bar{y}_{ij}^r \right] \tag{6.2}$$

is the expected net value w.r.t. the price scenarios $r = 1,2, \dots, R$, with probability $q^r$, of the incomes/expenses resulting from selling/buying energy $\bar{y}_{ij}^r$ at price $\pi_{ij}^r$ in the $m$ sessions of intraday markets, where $\bar{y}_{ij}^r = \sum_{s=1}^{S} p^s y_{ij}^{sr}$ is the expected value w.r.t. the generation scenarios $s = 1,2, \dots, S$ with probability $p^s$.

$$E_g[C_{deviation}(x, y)] = \sum_{s=1}^{S} p^s \sum_{i=1}^{24} c_i \left( \left[ x_i + \sum_{\forall j \mid i \in A(j)} \bar{y}_{ij}^s \right] - g_i^s \right) \tag{6.3}$$

is the expected value w.r.t. the generation scenarios $s = 1,2, \dots, S$ with probability $p^s$ of the cost of deviation that depends on the difference between the expected aggregated matched energy of the daily and intraday markets, $\left[x_i + \sum_{\forall j \mid i \in A(j)} \bar{y}_{ij}^s\right]$, with $\bar{y}_{ij}^s = \sum_{r=1}^{R} q^r y_{ij}^{rs}$ and the forecasted generation $g_i^s$ at each scenario $s$, penalized at cost $c_i$.

## III. CASE STUDY.

The maximization of the utility function (6) subject to constraints (1)-(5) defines a large-scale linear programming problem that can be conveniently solved with standard optimization tools. To validate the model it has been implemented using real data from a wind power plant of 16.2 MW and the set of parameters depicted in Table 1.

Table 2 : numerical values of the parameters used in the case study

| | | |
|---|---|---|
| $M$ | 6 | Sessions of intraday market |
| $b$ | 16.2MWh | Installed capacity |
| $\gamma_j$ | $\gamma_1 = 0.6$; $\gamma_2 = 0.55$; $\gamma_3 = 0.5$;<br>$\gamma_4 = 0.45$; $\gamma_5 = 0.4$; $\gamma_6 = 0.35$; | Decreasing bid factor |
| $\alpha$ | 0.9 | Minimum bid fraction |
| $\beta$ | 0.8 | Daily to intraday bid fraction |

Generation forecasts, used to formulate market offers, are provided by an expert meteorological company and updated continuously during the day. Error in the prediction received before daily market closes has been studied in order to construct scenarios on expected generation. Since observations can be assumed to be from an independent and identically distributed population, a bootstrapping procedure can be implemented by constructing a number of resamples of the observed dataset, obtained by random sampling with replacement from the original dataset. Using this procedure a random sample of 200 values has been generated and 64 scenarios for the prediction error have been constructed calculating the respective probabilities. The scenarios for the intraday market prices $\pi_{ij}^{r}$ have been adapted from Corchero and Heredia (2011) where all the available historical data of the sequence of market prices has been reduced in order to obtain suitable scenario sets. Initially, all the instances are equiprobable and, after applying the reduction algorithm of Gröwe-Kuska et al. (2003), the different subsets of scenarios and the respective probabilities are obtained. Data on daily market prices have been downloaded from the website of the independent Iberian Market Operator OMEL (2012). Two cases of daily market price curve have been considered, one "low" corresponding to the day October 4, 2010 and the other "high" corresponding to July 1, 2011, after a change in the situation of the Spanish electricity market. A representative deviation cost curves observed by the wind producer has been used in all the implementation of the model.

The resulting two stage stochastic optimization problem has 24 first-stage variables ($x_i$) 1.369.600 two-stage variables ($y_{ij}^{sr}$) and 3.520.024 constraints. It has been implemented in AMPL (Fourer et al. 2003) and solved with CPLEX (CPLEX (2008)) in a Fuji Rx200 56 workstation (2XCPUs Intel Xeon X5680 at 3.33 GH, 64Gb RAM) in less than 10m minutes.

# IV. RESULTS.

## Case 1: low price curve.

We first implemented the model using clearing price for daily market of October 4, 2010 and average deviation costs of September 2010. Figure 3 shows the value of the optimal bid to the daily market (first stage variables $x_i$) compared with the best available forecasting of the wind generation before daily market close at 10:00 a.m. (the parameter $\bar{e}_i$).

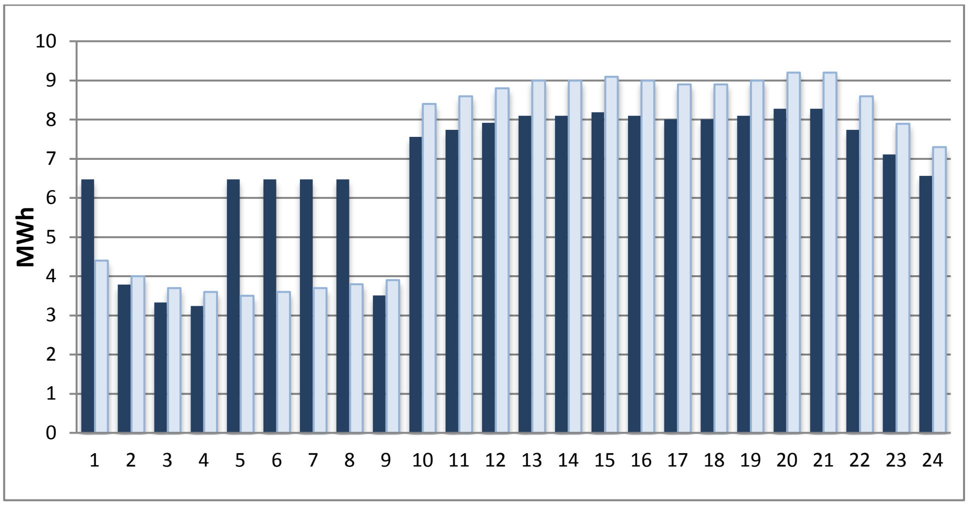


Figure 4: comparison of the daily bid and the forecasted wind generation. In dark blue, the optimal daily bid $x_i$. In light blue, the expected wind generation $\bar{e}_i$.

The optimal solution prescribes to offer the minimum quantity of energy in the majority of hours. That is because clearing price curve of daily market is very low (showing some zero) and it is better to sell it in the intraday market sessions in all hours but 1, 5, 6, 7 and 8. In those hours we are not offering the entire capacity: that is because some restrictions on transactions' volume and deviation costs are active.

## Case 2: high price curve.

We implemented the model again with daily market prices of July 1, 2011 and average deviation costs of June 2011. The economic crisis, Spanish carbon law and low wind production caused price market to increase remarkably in this period and produced a change in inter-hours volatility as well. We show in the following graph the price curves (mean values) and the correspondent solution to see how a change in price level affects the solution.

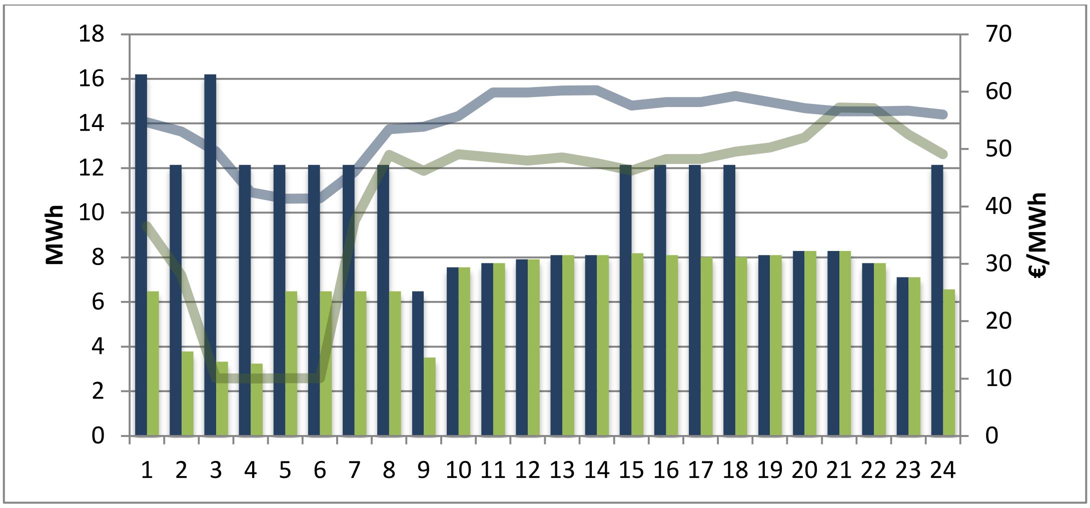


Figure 5: comparison of the sale bid (bars) to the daily market for the two cases considered, high prices (blue line) and low prices (green line).

The optimal solution obtained when daily market prices are greater and show a reduced volatility, prescribes to sell more in those hours where price differences between daily and intraday market can be exploited. A peak is reached in hour 3: in this case it is optimal to sell more in daily market and buy at a lower price in the cheapest session of intraday market exploiting price difference.

A comparison with the optimal solution previously obtained using the model including only generation scenarios is necessary to see the effects of including intraday price scenario in a context of high daily market prices.

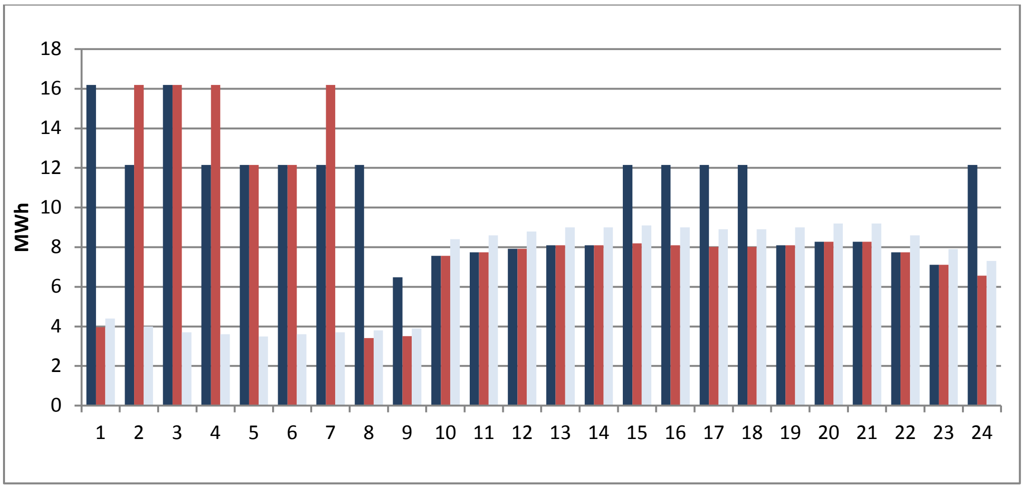


Figure 6: comparison between the sale bid to the day ahead market for the model with (dark blue) and without (red) scenarios for the intraday market prices, together with the expected wind generation $\bar{e}_i$ (light blue).

Again, keeping into account volatility in the market prescribes to be more conservative in some hours typically characterized by low prices and to be more aggressive in those hours that show lower clearing prices.

## The role of the deviation costs

To prove the importance of including the penalization component in the objective function we solve the full model including price scenarios and generation scenarios but eliminating the expected value of the losses due to deviation penalizations $E_{\pi,g}[C_{deviation}(x,y)]$ of the objective function (6), all the remaining restrictions being the same as before. The solution obtained (see Figure 7) is the same for hours 9 onward but is much more risky in the first eight hours when it recommends to sell total capacity in the daily market. Looking at the graph showing daily market price and deviation cost curves we can see in details where the results come from.

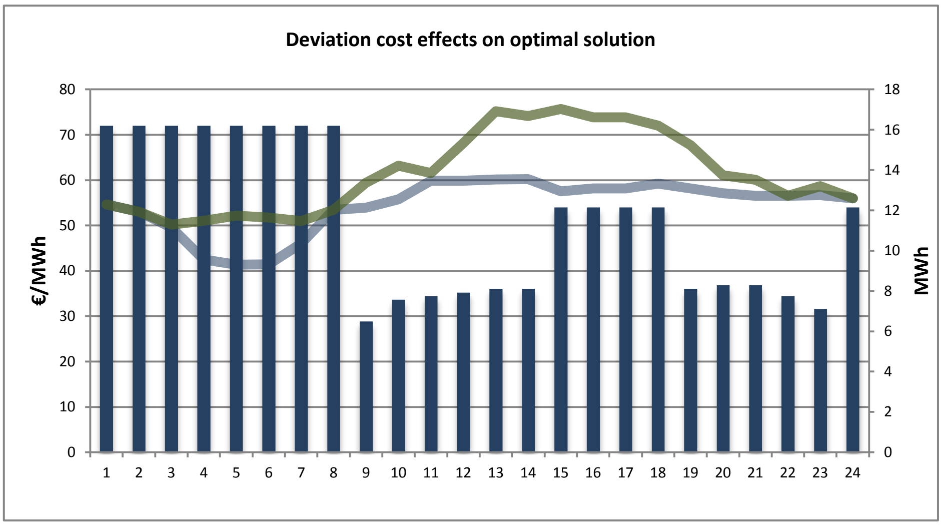


Figure 8: optimal sale bid to the daily market disregarding the deviation costs (6).The blue line represents daily market prices and the red line are the deviation costs.

Deviation costs only affects optimal sale bid for the first hours of the day when a lower number of intraday markets are available for adjustments. In this case, restrictions on transactions volumes make it impossible to annul the deviation by offering a final programming equal to the expected generation. In the rest of hours it is strictly optimal to sell rather than buy electricity, so that in any scenario the solution prescribes to buy energy up to total installed capacity. The final programming will be the total capacity sold in any hour of the day, while keeping into account deviation costs it will be equal or a bit slightly greater than expected generation: that is because deviation costs are higher than prices of the last sessions of intraday market. That let us believe that the deviation cost will have a greater and clearer impact on decisions on adjustment variables.

## The role of the generation forecast of 10 a.m.

One could think that the possibility to speculate depends on the type of prediction received: should a lower prediction leave enough room for more speculations? Lower bounds of any of the restrictions will change according to that. We use data on prediction sent in a day of bad wind conditions and see how the solution changes.

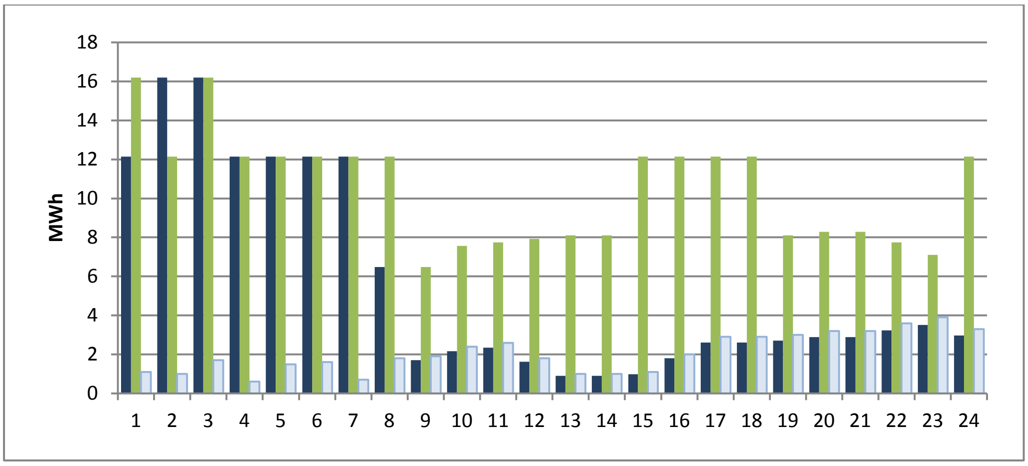


Figure 9: Change in optimal bid due to low generation prediction. Dark blue, optimal bid with low forecasted generation; green, optimal bid high expected generation; light blue, low generation forecast.

The effect on the optimal solution is controversial:

- On one hand, a lower generation forecast implies a greater risk to incur in penalization when inflating the sale bid in the daily market. So some restrictions that were not active will now become active. That is the case of hours 1, 8, 15, 16, 17, 18 and 24.
- On the other hand, the feasible region of the problem becomes bigger and some greater optimal hourly sale bid can be obtained as in hour 2.

The solution prescribes to offer the minimum in all those hours that are risky in terms of price differences and higher deviation costs: when speculating is difficult because of high deviation costs and transaction sizes is better not selling too much in the day-ahead market not to incur in undesirable losses

# V. VALUE OF THE STOCHASTIC SOLUTION.

The value of the stochastic solution (VSS, Birge and Louveaux (1997)) can be interpreted as the potential benefit from solving the stochastic program over solving a deterministic program in which expected values have replaced random parameters.

The VSS is the difference between the goal value for the stochastic problem, and the average goal value over all scenarios when the non-recourse decisions (variables $x_i$ in our problem) are fixed to their values in the expected value problem. If this difference is small, then that indicates that using the solution of the expected value problem will likely lead to a "pretty good" solution to actual stochastic problem. In other words, the randomness does not play a very significant role. This is not the same as saying that the amount of randomness in the problem is "small".

In our model we introduced two sources of randomness, one due to prediction error (represented with 64 sampled values of the random variable) and the other due to volatility in intraday market prices (represented through 200 sampled values), with a total of 12800 scenarios. We maximize the utility function $f_{\pi,g}(x,y)$ (6) and obtain the optimal solution $x^*$, $y^*$ that will provide an optimal expected utility of $f_{\pi,g}(x^*,y^*)$.

We will now maximize the expected utility, i.e. we will solve the problem (1)-(6) considering just one scenario for intraday prices and generation with a value of $\bar{\pi}_{ij} = \sum_{r=1}^{R} q^r \, \pi_{ij}^r$ and $\bar{g}_i = \sum_{s=1}^{S} p^s \, g_i^s$ respectively:

$$\max \bar{f}(x,y) = \sum_{i=1}^{24} \lambda_i x_i + \sum_{j=1}^{M} \sum_{i\in A(j)} \bar{\pi}_{ij} y_{ij} - c_i \sum_{i=1}^{24} \left[ x_i + \sum_{\forall j \mid i\in A(j)} y_{ij} - \bar{g}_i \right]$$

$$\text{s.t.} \quad \alpha \bar{e}_i \le x_i \le b \qquad i = 1,\dots,24$$

$$y_{i1} \ge -\beta x_i \qquad i = 1,\dots,24$$

$$\bar{g}_i \le x_i + \sum_{\forall j \mid i\in A(j)} y_{ij} \le b \quad i = 1,\dots,24$$

$$0 \le x_i + \sum_{\forall j \le n \mid i\in A(j)} y_{ij} \le b \quad i = 1,\dots,24 \quad n = 1,\dots,5$$

$$-\gamma_j b \le y_{ij} \le \gamma_j b \qquad i \in A(j)\; j = 1,\dots,M$$

We denote by $\bar{x}^*$,$\bar{y}^*$ the optimal solution of this problem and $\bar{f}(\bar{x}^*,\bar{y}^*)$ the optimal value of the objective function. Then the Value of the Stochastic Solution (VSS) is defined as:

$$\text{VSS} = f_{\pi,g}(x^*,y^*) - \bar{f}(\bar{x}^*,\bar{y}^*)$$

We calculate the VSS of the model for both observations of intraday market prices and deviation costs considered.

- Case 1 with data from October 2011 (low prices) gives a $VSS$ value of:

$$\text{VSS} = f_{\pi,g}(x^*,y^*) - \bar{f}(\bar{x}^*,\bar{y}^*) = 12.155€ - 12.032€ = 133€$$

- Case 2 with data from July 2011 (high prices) gives a $VSS$ value of:

$$\text{VSS} = f_{\pi,g}(x^*,y^*) - \bar{f}(\bar{x}^*,\bar{y}^*) = 11.269€ - 9.145€ = 2.124€$$

We are maximizing the daily profits of a wind producer for one of its plant: the improvement in the solution is remarkable if we consider that it can be achieved daily and that the same optimization method can be applied to all other wind farms in operation. The results suggest that it is worth introducing randomness in the model as in less than 10 minutes of CPU we can achieve an increment in the profits that ranges from 1% to the 23%.

# CONCLUSIONS.

The objective of this work is to look for new optimal commercial strategies for wind power producers, required to increase their performance in the production market.

The results obtained by implementing a model including both generation and intraday market price scenarios provide important information on common practice currently used in the market. It is not optimal to construct the sale bid systematically inflating the last prediction received before market closes and buy the default energy quantity in first and second sessions of the intraday market. That is quite risky in a system where change in price level and volatility is taking place and uncertainty calls for prudency. Including in the objective function randomness due to error in generation predictions, we are trying to limit the risk of incurring in penalization and create more room to take profit of the electricity multi-market structure (the greater the knowledge on the generation distribution, the greater the possibility to operate efficiently into the market).

The results show that optimal solution does not depend only on difference in price level in the different sessions of the market but also on transactions' size and deviation costs. We can state that expected difference in price level in general determines what to do: optimal solutions generally prescribe to inflate predictions when daily market price is greater than intraday markets' prices, while offering the minimum when the opposite occurs.

For this reason we have included scenarios for intraday market prices. That allows considering many possible market circumstances and relationship between price levels in the different market sessions.

The solution obtained varies according to price scenarios, prescribing to be prudent where there is room for speculation due to a positive difference in price levels. Only when the probability of daily market price to be greater than intraday markets' prices is high, typically during the off-peak hours, and no restriction on transactions' size is active, the solution suggest to offer the maximum.

Deviation costs has to be included to be considered that, if a producer does not have enough room to adjust the final programming and sell too much in the daily market, he would sensibly reduce his profit.

Solutions obtained including price scenarios are more prudent than the ones only accounting for generation scenarios.

Through the calculation of the Value of the Stochastic Solution we have showed that there is a considerable benefit to include both generation and price scenarios in the objective function.

Further improvement of the model could be obtained considering the correlation between the different market price curves to better modeling the dependency on the solution on market volatility.

Moreover, the model has been implemented considering only positive deviation costs, since it was adequate in a context of low market demand. It would be interesting to include in the model some scenarios on relationship between energy demand and offer, and associated deviation costs.

Finally, it is interesting to remark that the model presented gives the optimal sale bid to the daily market, while the bid to the intraday markets are considered as second stage variable in the stochastic programming model and, as such, they cannot be used to arrange the bid to the intraday markets. But of course it should be possible to arrange a sequence of stochastic programming problems $(P_j)$ similar to the one proposed here, one per session $j$ of the intraday markets, to find the optimal sale bid to each hour $i \in A(j)$ considered in the intraday market $j$, namely $y^*_{ij}$. In this strategy, problem $(P_j)$ should be solved between the closure of intraday markets $j-1$ and $j$, with the last forecasting of both the wind generation $g$ and intraday market prices $\pi_k$, $k > j$. This "cascade" solution for daily and intraday markets would determine the entire commercial strategy of a wind producer.

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## References

Birge J.R., Louveaux F. (1997) Introduction to Stochastic Programming, Springer.

Corchero C., Heredia F.J. (2011) Optimal Daily Bidding in the MIBEL's Multimarket Energy Production System,*Proceedings of the 7th Conference on European Energy Market EEM10*, Madrid, IEEE, pp. 1 - 6 , ISBN: 978-1-4244-6838-, DOI: 10.1109/EEM.2010.5558714

CPLEX (2008), CPLEX Optimization subroutine library guide and reference. Version 11.0, CPLEX Division, ILOG Inc., Incline Village, NV, USA.

Fourer R., Gay D. M., Kernighan B.W. (2003) AMPL: A modeling language for mathematical programming, CA: Brooks/Cole-Thomson Learning, 2nd ed.

García-González J., Moraga R., Matres L., Mateo A. (2008) Stochastic Joint Optimization of Wind Generation and Pumped-Storage Units in an Electricity Market. IEEE TRANSACTIONS ON POWER SYSTEMS, VOL. 23, NO. 2, MAY 2008. http://dx.doi.org/10.1109/TPWRS.2008.919430

Gröwe-Kuska N., Heitsch H., and Römisch W. (2003) Scenario reduction and scenario tree construction for power management problems, in Power Tech Conference Proceedings, 2003 IEEE Bologna, vol. 3, 23-26 June 2003.

Holttinen H. (2005) Optimal electricity market for wind power. Energy Policy, Volume 33, Issue 16, November 2005, Pages 2052-2063. http://dx.doi.org/10.1016/j.enpol.2004.04.001

Li G, Shi J. (2012) Agent-based modeling for trading wind power with uncertainty in the daily wholesale electricity markets of single-sided auctions. Appl Energy, http://dx.doi.org/10.1016/j.apenergy.2012.04.022

MacGill I. (2010) Electricity market design for facilitating the integration of wind energy: Experience and prospects with the Australian National Electricity Market Energy Policy, Volume 38, Issue 7, July 2010, Pages 3180-3191. http://dx.doi.org/10.1016/j.enpol.2009.07.047,

Morales J.M., Conejo A.J., Pérez-Ruiz J. (2010) Short-Term Trading for a Wind Power Producer. IEEE TRANSACTIONS ON POWER SYSTEMS, VOL. 25, NO. 1, FEBRUARY 2010. http://dx.doi.org/10.1109/TPWRS.2009.2036810

Moreno M.A., Bueno M., Usaola J. (2012) Evaluating risk-constrained bidding strategies in adjustment spot markets for wind power producers Electrical Power and Energy Systems 43 (2012) 703–711. http://dx.doi.org/10.1016/j.ijepes.2012.05.059

OMIE (2012) Operator of the Spot Iberian Electricity Market. http://www.omie.es

Pinson P., Chevallier Ch., Kariniotakis G.N. (2007) Trading Wind Generation From Short-Term Probabilistic Forecasts of Wind Power. IEEE TRANSACTIONS ON POWER SYSTEMS, VOL. 22, NO. 3, AUGUST 2007. http://dx.doi.org/10.1109/TPWRS.2007.901117

Rivier J. (2010) Electricity market participation of wind farms: the success story of the Spanish pragmatism Energy Policy 38 (2010) 3174–3179 http://dx.doi.org/10.1016/j.enpol.2009.07.032